CLAIM AMENDMENTS

Please amend claims 1, 3, 5, 7-8, 11-38, 40 and 60-61 to read as follows. Please cancel claims 2, 4, 6, 39, 41 and 43. All other claims are unamended.

- 1 1. (currently amended) A method for automating the
- 2 identification of meaningful features and the formulation of
- 3 expert rules for classifying magnetocardiography data, comprising-
- 4 the step of:
- 5 applying a <u>kernel_wavelet_transform</u> to sensed data acquired
- 6 from sensors sensing electromagnetic <u>fields generated by a</u>
- 7 patient's heart activity, resulting in transformed wavelet domain
- 8 data;
- 9 applying a kernel transform to said wavelet domain data,
- 10 resulting in transformed data; and, prior to
- identifying said meaningful features and formulating said
- 12 expert rules from classifying said transformed data, using machine
- 13 learning.
- 1 2. (cancelled)
- 1 3. (currently amended) The method of claim 1, for classifying-
- 2 | magneto cardiography data, further comprising the step of:
- 3 acquiring said sensed data from magnetic sensors proximate a
- 4 patient's heart.
- 1 4. (cancelled)
- 1 5. (currently amended) The method of claim 1, further

- 2 | comprising the step of:
- 3 classifying said transformed data using machine learning.
- 1 6. (cancelled)
- 1 7. (currently amended) The method of claim 3, further
- 2 | comprising the step of:
- 3 classifying said transformed data using machine learning.
- 1 8. (currently amended) The method of claim 4, further
- 2 | comprising the step of:
- 3 classifying said transformed data using machine learning.
- 1 9. (original) The method of claim 1, said kernel transform
- 2 satisfying Mercer conditions.
- 1 10. (original) The method of claim 1, said kernel transform
- 2 comprising a radial basis function.
- 1 11. (currently amended) The method of claim 1, said step of
- 2 applying a kernel transform comprising the steps of:
- 3 assigning said transformed data to a first hidden layer of a
- 4 neural network;
- 5 applying training data descriptors as weights of said first
- 6 hidden layer of said neural network; and
- 7 calculating weights of a second hidden layer of said neural
- 8 network numerically.
- 1 | 12. (currently amended) The method of claim 11, said-step of
- 2 calculating said weights of said second hidden layer numerically
- 3 | further comprising the step of:
- 4 calculating said weights of said second hidden layer using

- 5 kernel ridge regression.
- 1 | 13. (currently amended) The method of claim 1, said step of
- 2 applying a kernel transform comprising-the step of:
- 3 applying a direct kernel transform.
- 1 14. (currently amended) The method of claim 1, further
- 2 | comprising the step of:
- 3 classifying said transformed data using a self-organizing map
- 4 (SOM).
- 1 15. (currently amended) The method of claim 1, further
- 2 comprising—the step of:
- 3 classifying said transformed data using a direct kernel self-
- 4 organizing map (DK-SOM).
- 1 16. (currently amended) The method of claim 1, further
- 2 | comprising the step of:
- 3 classifying said transformed data using kernel partial least
- 4 square (K-PLS) machine learning.
- 1 17. (currently amended) The method of claim 1, further
- 2 | comprising the step of:
- 3 classifying said transformed data using direct kernel partial
- 4 least square (DK-PLS) machine learning.
- 1 $\,$ 18. (currently amended) $\,$ The method of claim 1, further
- 2 comprising the step of:
- 3 classifying said transformed data using a least-squares
- 4 support vector machine (LS-SVM).
- 1 19. (currently amended) The method of claim 1, further

- 2 comprising the step of:
- 3 classifying said transformed data using a direct kernel
- 4 principal component analysis (DK-PCA).
- 1 20. (currently amended) The method of claim 1, further
- 2 comprising the step of:
- 3 classifying said transformed data using a support vector
- 4 machine (SVM / SVMLib).
- 1 | 21. (currently amended) The method of claim 20, said step of
- 2 classifying said transformed data using a support vector machine
- 3 (SVM / SVMLib) further comprising the step of:
- 4 setting an SVMLib regularization parameter, C, to C=1/ λ , for
- 5 an n data kernel, wherein:
- 6 said λ is proportional to said n to a power of 3/2
- 1 | 22. (currently amended) The method of claim 20, said—step of
- 2 classifying said transformed data using a support vector machine
- 3 (SVM / SVMLib) further comprising the step of:
- setting an SVMLib regularization parameter, C, to C=1/ λ , for
- 5 an n data kernel, wherein:

$$\lambda = \min \left\{ 1; \left(\frac{n}{1500} \right)^{\frac{3}{2}} \right\}$$

- 1 23. (currently amended) The method of claim 12, said step of
- 2 converting transforming said sensed data into a said wavelet
- 3 domain data comprising the step of:
- 4 applying a Daubechies wavelet transform to said sensed data.

- 24. (currently amended) The method of claim 12, further 1 comprising-the step of: selecting features from said wavelet domain data which 3 4 improve said classification of magnetocardiography data. 25. (currently amended) The method of claim 24, said-step of 1 selecting said features further comprising-the step of: 2 3 eliminating selected undesirable features from said wavelet data. (currently amended) The method of claim 25, said-step-of 2 eliminating selected undesirable features comprising the step of: 3 eliminating outlying data from said wavelet data. 1 27. (currently amended) The method of claim 25, said step of 2 eliminating selected undesirable features comprising the step of: 3 eliminating cousin descriptors from said wavelet data. 1 28. (currently amended) The method of claim 24, said step of 2 selecting said features further comprising the step of: 3 retaining only selected desirable features from said wavelet 4 data. 29. (currently amended) The method of claim 28, said step of 1 retaining only selected desirable features further comprising-the-
- using a training data set; and

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steps of:

- 5 using a validation data set for confirming an absence of
- 6 over-training of said training set.
- 1 | 30. (currently amended) The method of claim 29, said step of

- retaining only selected desirable features further comprising—the—

 3 steps of:
- 4 using a genetic algorithm to obtain an optimal subset of
- 5 features from said training data set; and
- 6 using said genetic algorithm for evaluating performance on
- 7 said validation date set.
- 1 31. (currently amended) The method of claim 29, said step of
- 2 retaining only selected desirable features further comprising the
- 3 steps of:
- 4 measuring sensitivities of said features from said wavelet
- 5 data in relation to a predicted responses of said features; and
- 6 eliminating lower-sensitivity features from among said
- 7 features with comparatively lower sensitivity than other, higher-
- 8 sensitivity features from among said features.
- 1 | 32. (currently amended) The method of claim 24, said-step of
- 2 selecting said features further comprising the steps of:
- 3 eliminating selected undesirable features from said wavelet
- 4 data; and
- 5 retaining only selected desirable features from said wavelet
- 6 data.
- $1\ \ 33.$ (currently amended) The method of claim 1, further
- 2 | comprising the step of:
- 3 normalizing said sensed data.
- 1 | 34. (currently amended) The method of claim 33, said step of
- 2 normalizing said sensed data comprising the step of:

- 3 Mahalanobis scaling said sensed data.
- 1 35. (currently amended) The method of claim 1, further
- 2 | comprising the step of:
- 3 centering a kernel of said kernel transform.
- 1 | 36. (currently amended) The method of claim 35, said-step of
- 2 centering said kernel comprising the steps of:
- 3 subtracting a column average from each column of a training
- 4 data kernel;
- 5 storing said column average for later recall, when centering
- 6 a test data kernel.
- 7 subtracting a row average form each row of said training data
- 8 kernel.
- 1 37. (currently amended) The method of claim 36, said step of
- 2 centering said kernel further comprising the steps of:
- 3 adding said stored column average to each column of said test
- 4 data kernel:
- 5 for each row, calculating an average of said test data
- 6 kernel; and
- 7 subtracting said row average from each horizontal entry of
- 8 said test data kernel.
- 1 | 38. (currently amended) An apparatus for automating the
- 2 | identification of meaningful features and the formulation of
- 3 expert rules for classifying magnetocardiography data, comprising
- 4 computerized storage, processing and programming for:
- 5 applying a kernel-wavelet transform to sensed data acquired

- 6 | from sensors sensing electromagnetic fields generated by a
- 7 patient's heart activity, resulting in transformed wavelet domain
- 8 data;
- 9 applying a kernel transform to said wavelet domain data,
- 10 resulting in transformed data; and, prior to
- identifying said meaningful features and formulating said
- 12 expert rules from classifying-said transformed data, using machine
- 13 learning.
- 1 39. (cancelled)
- 1 40. (currently amended) The apparatus of claim 38, for-
- 2 classifying magneto-cardiography data, further comprising an input
- 3 for:
- 4 acquiring said sensed data from magnetic sensors proximate a
- 5 patient's heart.
- 1 41. (cancelled)
- 1 42. (original) The apparatus of claim 38, further comprising
- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using machine learning.
- 1 43. (cancelled)
- 1 44. (original) The apparatus of claim 40, further comprising
- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using machine learning.
- 1 45. (original) The apparatus of claim 41, further comprising
- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using machine learning.

- 1 46. (original) The apparatus of claim 38, wherein kernel
- 2 transform satisfies Mercer conditions.
- 1 47. (original) The apparatus of claim 38, said kernel transform
- 2 comprising a radial basis function.
- 1 48. (original) The apparatus of claim 38, said computerized
- 2 storage, processing and programming for applying a kernel
- 3 transform further comprising computerized storage, processing and
- 4 programming for:
- 5 assigning said transformed data to a first hidden layer of a
- 6 neural network;
- 7 applying training data descriptors as weights of said first
- 8 hidden layer of said neural network; and
- 9 calculating weights of a second hidden layer of said neural
- 10 network numerically.
 - 1 49. (original) The apparatus of claim 48, said computerized
 - 2 storage, processing and programming for calculating said weights
 - 3 of said second hidden layer numerically further comprising
- 4 computerized storage, processing and programming for:
- 5 calculating said weights of said second hidden layer using
- 6 kernel ridge regression.
- 1 50. (original) The apparatus of claim 38, said computerized
- 2 storage, processing and programming for applying a kernel
- 3 transform further comprising computerized storage, processing and
- 4 programming for:
- 5 applying a direct kernel transform.

- 1 51. (original) The apparatus of claim 38, further comprising
- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using a self-organizing map
- 4 (SOM).
- 1 52. (original) The apparatus of claim 38, further comprising
- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using a direct kernel self-
- 4 organizing map (DK-SOM).
- 1 53. (original) The apparatus of claim 38, further comprising
- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using kernel partial least
- 4 square (K-PLS) machine learning.
- 1 54. (original) The apparatus of claim 38, further comprising
- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using direct kernel partial
- 4 least square (DK-PLS) machine learning.
- 1 55. (original) The apparatus of claim 38, further comprising
- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using a least-squares
- 4 support vector machine (LS-SVM).
- 1 56. (original) The apparatus of claim 38, further comprising
- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using a direct kernel
- 4 principal component analysis (DK-PCA).
- 1 57. (original) The apparatus of claim 38, further comprising

- 2 computerized storage, processing and programming for:
- 3 classifying said transformed data using a support vector
- 4 machine (SVM / SVMLib).
- 1 58. (original) The apparatus of claim 57, said computerized
- 2 storage, processing and programming for classifying said
- 3 transformed data using a support vector machine (SVM / SVMLib)
- 4 transform further comprising computerized storage, processing and
- 5 programming for:
- 6 setting an SVMLib regularization parameter, C, to $C=1/\lambda$, for
- 7 an n data kernel, wherein:
- 8 said λ is proportional to said n to a power of 3/2
- 1 59. (original) The apparatus of claim 57, said computerized
- 2 storage, processing and programming for classifying said
- 3 transformed data using a support vector machine (SVM / SVMLib)
- 4 transform further comprising computerized storage, processing and
- 5 programming for:
- 6 setting an SVMLib regularization parameter, C, to C=1/ λ , for
- 7 an n data kernel, wherein:

$$\lambda = \min\left\{1; \left(\frac{n}{1500}\right)^{\frac{3}{2}}\right\}$$

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- 1 | 60. (original) The apparatus of claim 3839, said computerized
- 2 storage, processing and programming for converting transforming
- 3 | said sensed data into a-said wavelet domain data comprising
- 4 computerized storage, processing and programming for:

- 5 applying a Daubechies wavelet transform to said sensed data.
- 1 | 61. (currently amended) The apparatus of claim $38\frac{39}{39}$, further
- 2 computerized storage, processing and programming for:
- 3 selecting features from said wavelet <u>domain</u> data which
- 4 improve said classification of magneto cardiography data.
- 1 62. (original) The apparatus of claim 61, said comprising
- 2 computerized storage, processing and programming for selecting
- 3 said features further comprising computerized storage, processing
- 4 and programming for:
- 5 eliminating selected undesirable features from said wavelet
- 6 data.
- 1 63. (original) The apparatus of claim 62, said comprising
- 2 computerized storage, processing and programming for eliminating
- 3 selected undesirable features comprising computerized storage,
- 4 processing and programming for:
- 5 eliminating outlying data from said wavelet data.
- 1 64. (original) The apparatus of claim 62, said computerized
- 2 storage, processing and programming for eliminating selected
- 3 undesirable features comprising computerized storage, processing
- 4 and programming for:
- 5 eliminating cousin descriptors from said wavelet data.
- 1 65. (original) The apparatus of claim 61, said computerized
- 2 storage, processing and programming for selecting said features
- 3 further comprising computerized storage, processing and
- 4 programming for:

- 5 retaining only selected desirable features from said wavelet
- 6 data.
- 1 66. (original) The apparatus of claim 65, said computerized
- 2 storage, processing and programming for retaining only selected
- 3 desirable features further comprising computerized storage,
- 4 processing and programming for:
- 5 using a training data set; and
- 6 using a validation data set for confirming an absence of
- 7 over-training of said training set.
- 1 67. (original) The apparatus of claim 66, said computerized
- 2 storage, processing and programming for retaining only selected
- 3 desirable features further comprising computerized storage,
- 4 processing and programming for:
- 5 using a genetic algorithm to obtain an optimal subset of
- 6 features from said training data set; and
- 7 using said genetic algorithm for evaluating performance on
- 8 said validation date set.
- 1 68. (original) The apparatus of claim 66, said computerized
- 2 storage, processing and programming for retaining only selected
- 3 desirable features further comprising computerized storage,
- 4 processing and programming for:
- 5 measuring sensitivities of said features from said wavelet
- 6 data in relation to a predicted responses of said features; and
- 7 eliminating lower-sensitivity features from among said
- 8 features with comparatively lower sensitivity than other, higher-

- 9 sensitivity features from among said features.
- 1 69. (original) The apparatus of claim 61, said computerized
- 2 storage, processing and programming for selecting said features
- 3 further comprising computerized storage, processing and
- 4 programming for:
- 5 eliminating selected undesirable features from said wavelet
- 6 data; and
- 7 retaining only selected desirable features from said wavelet
- 8 data.
- 1 70. (original) The apparatus of claim 38, further comprising
- 2 computerized storage, processing and programming for:
- 3 normalizing said sensed data.
- 1 71. (original) The apparatus of claim 70, said computerized
- 2 storage, processing and programming for normalizing said sensed
- 3 data comprising computerized storage, processing and programming
- 4 for:
- 5 Mahalanobis scaling said sensed data.
- 1 72. (original) The apparatus of claim 38, further comprising
- 2 computerized storage, processing and programming for:
- 3 centering a kernel of said kernel transform.
- 1 73. (original) The apparatus of claim 72, said computerized
- 2 storage, processing and programming for centering said kernel
- 3 comprising computerized storage, processing and programming for:
- 4 subtracting a column average from each column of a training
- 5 data kernel;

- 6 storing said column average for later recall, when centering
- 7 a test data kernel.
- 8 subtracting a row average form each row of said training data
- 9 kernel.
- 1 74. (original) The apparatus of claim 73, said computerized
- 2 storage, processing and programming for centering said kernel
- 3 further comprising computerized storage, processing and
- 4 programming for:
- 5 adding said stored column average to each column of said
- 6 test data kernel;
- 7 for each row, calculating an average of said test data
- 8 kernel; and
- 9 subtracting said row average from each horizontal entry of
- 10 said test data kernel.